A Speculative Approach For Brain Tumor Detection Using Image Processing

Vaishnavi Jambhale
Information Technology
(of Affiliation)
K.C. College of Engineering
(of Affiliation)
Thane, India
jambhalevaishnavi@kccemsr.edu.in

Janhavi Panvekar
Information Technology
(of Affiliation)
K.C. College of Engineering
(of Affiliation)
Thane, India
panvekarjanhavi@kccemsr.edu.in

Supriya Prajapati
Information Technology
(of Affiliation)
K.C. College of Engineering
(of Affiliation)
Thane, India
prajapatisupriya@kccemsr.edu.in

Sheetal Jadhav (Guide)
Assistant Professor
Information Technology
(of Affiliation)
K.C. College of Engineering
(of Affiliation)
Thane, India
sheetal.jadhav@kccemsr.edu.in

***Abstract*— The brain is the essential organ within the human body, controlling and regulating all crucial existing functions, and a tumour is a mass of tissue formed through an accumulation of extraordinary cells that preserve to grow. A brain tumour is a tumour that has formed within the brain or has migrated there, for which no primary cause has been identified to date. Through the study it has been found that worldwide brain tumours make up only 1.8% of total reported tumours, the death rate of malignant brain tumours is very high because of their formation in the most essential organ of the body. Hence, there is a need to detect brain tumours at early stages with greater accuracy.**

We have thus proposed a system which will assess brain tumors from MRI scans for the management of brain tumor diagnosis. In this study, we will implement a model that, pre-processes the image, performs the post- processing by applying Morphological operation, segments the image using contour based edge detection and then finally classifies the tumors using EfficientNet which is a model of convolutional neural network architecture and gives the high degree of accuracy.

Keywords—Brain tumor, Image processing, Morphology, Classification, Contour-based segmentation, EfficientNet.

I. INTRODUCTION

The brain is the primary processing organ in the human body, governing cognition, memory, vision, and respiration. To protect the brain from outside forces, millions of cells stack in a rigid cranium. This vital organ derives from the brain stem. As a result, any abnormality in the brain may endanger human health. A brain tumour is the most common and life-threatening of the various brain problems these days. About 11,000 people are diagnosed with a brain tumour every year. A brain tumour affects approximately 1 lakh of 50 thousand cancer patients each year. A brain tumour develops as a result of abnormal cell growth in the brain. Treatment for brain tumours varies according to their location, size, and type. The most common treatment for a brain tumour is surgery, which has no neurological side effects. To diagnose brain tissues, several methods are used, including computed tomography (CT) scanning, magnetic resonance imaging (MRI), and electroencephalography (EEG). MRI technology uses a magnetic field and radio waves to produce images of internal organs. The images provide critical information on brain tissue structure due to the high resolution of this approach. Because manual categorization of MRI images in complex situations is difficult and error-prone, MRI imaging identifying brain tumours and comparing their tissues to healthy cells is not a simple process and should be performed by a trained professional. The goal of our project is to detect and classify brain tumours accurately using various techniques involving image processing, morphological operations, segmentation, and classification. These techniques involve pre-processing of MRI scans obtained from an online cancer dataset, and we use the proposed algorithms to achieve the desired results. Brainsurgeons, doctors, and other healthcare professionals can use our system. The system is expected to improve the current brain tumour screening procedure while also potentially lowering healthcare costs by reducing the need for follow-up procedures.

II. LITERATURE SURVEY

This project's methodology includes data pre-processing, model building, and evaluation. The CNN model is built using the VGG16 architecture and trained on pre-processed data for 10 epochs with a batch size of 64. The model is evaluated using the receiver's area under the operating characteristic curve (AUC). According to the findings of this project, the CNN model with VGG16 architecture achieves an AUC of 0.92 for classifying brain tumour images into four distinct classes [1].

This study uses histogram normalisation, thresholding, fast fourier transform (FFT), and fast fourier transform (FFT) techniques to develop brain tumour identification utilising advanced morphological methodologies and implement it on ground truth images for validation. In this study, the statistical parameters as well as the length, area, and brain volume of the tumour were calculated. Additionally, the proposed method has been evaluated against the K-NN, NSC IN Gaussian Case, and K-Means with Euclidian [9].

The paper presents a deep learning-based method for segmenting and classifying brain tumours in MRI scans. They began by preprocessing images with image augmentation and the Gaussian blur filter. The segmentation was then performed using binary thresholding. Morphological operations were used to extract features. Finally, CNN was used to classify the brain MRI as normal or abnormal. The model was trained with 255 brain MRIs, 155 of which contain tumours and 98 of which are healthy, and achieve 97% accuracy [10].

Table I : Literature Survey of different Deep Learning Approaches

Author	Techniques Used	Performance
(Saikat Sundar Pal et al., 2023) [1]	VGG16	Accuracy - 92.75 %
(Priyanka Jain et al., 2022) [2]	Anisotropic diffusion filtering technique	SNR(Signal to Noise Ratio) – 16.4767
(Shtwai Alsubai et al., 2022) [3]	CNN - LSTM	Accuracy - 99.1 %
(Mohammed Rasool et al., 2022) [4]	GoogleNet + SVM	Accuracy – 98.1 %
(Praveena, K. et al., 2022) [5]	DWT, GLCM, ANFIS Classifier	Accuracy – 94.12 %
(Reddy, G. P. et al., 2022) [6]	FCM, KFCM, DWT, SVM	Accuracy - 97.96 %
(Marzieh Ghahramani et all., 2022) [7]	Levenberg-Marquardt algorithm (LMA), BPNN, GLCM	Accuracy – 98.7 %
(T. Balamurugan et al., 2022) [8]	GLCM, FCM-GMM, LuNet, VGG16	Accuracy – 99.7 %
(K Sudha Rani et al., 2022) [9]	Advanced Morphological Techniques, FFT	Accuracy – 92.85 %
(Doshi Jeel Alpeshkumar et al., 2021) [10]	Morphological operations, CNN	Accuracy – 83.23 %

III. PROPOSED METHODOLOGY

The proposed method is able to detect even very low intensity parts of the image. Detecting the tumour is effectively implemented with the aid of pre-processing, morphological techniques and contour based segmentation. Morphological techniques are a set of image processing operations used to analyze the geometric structure of objects within an image. Before applying morphological operations, pre-processing is carried out with Gray-scale conversion, Gaussian blur effect and thresholding. Contour-based segmentation using edge detection is a popular technique for separating objects from their background in an image.

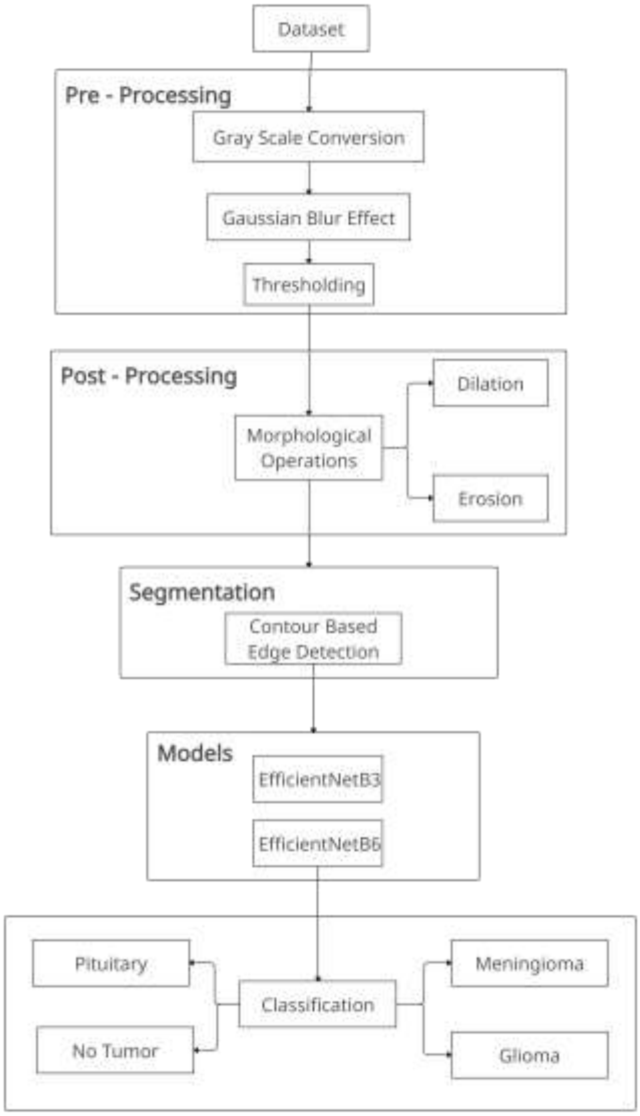

Fig. 1 : Proposed Model Architecture

IV. IMPLEMENTATION

Taking into account all of the various methods for implementing this given problem statement of Brain Tumor classification, we created a workflow that incorporates all of the previously mentioned work on the related subject. This section outlines the steps we took to complete this project. In our project, we collected enough data to help train the model, which ensures that the model will not be over-fitted, and then we implemented a model that, pre-processes the image, performs the post-processing by applying Morphological operation, segments the image using contour-based edge detection, and then finally classifies the tumors using EfficientNet which is a model of convolutional neural network architecture.

A. Dataset

The dataset named "Brain Tumor Classification (MRI)" is taken from the Kaggle website. The folder contains MRI scan data. The images were already split into Training and Testing folders and in total there were 3264 images. Each folder has four subfolders. These folders have MRIs of respective tumour classes which are meningioma (937 images), glioma (926 images), pituitary (901 images) and no (500 images) tumour. The images are of different shapes and these image are resized to 224x224.

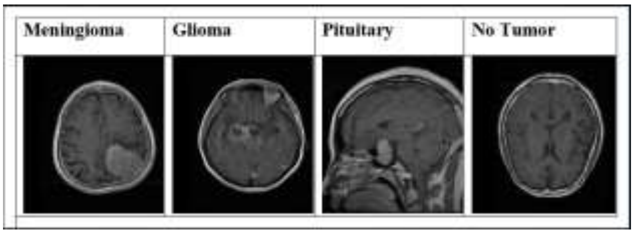

Fig. 2 : Dataset images of different classes

B. Image processing

The preprocessing stage of our project mainly includes Grayscale conversion, Gaussian Blur effect and Thresholding. In the Grayscale conversion, the simplification of the images to grayscale is done using OpenCV in Python and for that, we have used the cv2.cvtColor() function with the cv2.COLOR_RGB2GRAY flag. Further, we have applied the Gaussian blur effect to reduce image noise and smooth out sharp edges, which is implemented using the GaussianBlur function by specifying a kernel size of 5x5 and a sigma value of 0. Then to separate objects or regions in an image based on their intensity values we used the threshold function by specifying a threshold value of 45. Hence, Pixels with intensities greater than 45 are set to 255 and those below are set to 0, which creates a binary image.

The morphological operations such as erosion and dilation are utilised in post-processing. These functions will remove all of the low-intensity pixels from the image and extract the border pixels. The Erosion function removes minor details from the binary image and even reduces the size of the Regions of Interest (ROI). Each area's borders can be created by subtracting the eroded image from the original image. The Dilation function adds a structuring element to the binary image, resulting in a new binary image.

Segmentation is achieved using contour-based edge detection where the goal is to discover the largest contour and draw the border. Further, the obtained region of interest is isolated from the unwanted parts by finding the largest contour's extreme points. The resulting image will be cropped and devoid of any noise.

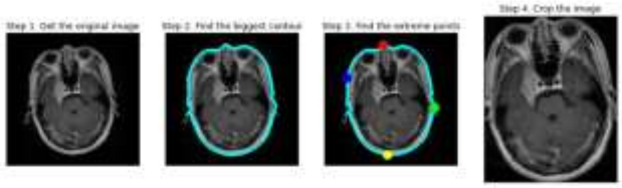

Fig. 3 : Cropped image obtained after preprocessing

C. Modeling

The cropped images obtained from the aforementioned image processing phase are stored in a new directory. Then these images are fed to the ImageDataGenerator class of the Keras library which will allow a model to receive new variations of the images at each epoch and it will also help the model generalise to new data more effectively by exposing it to broader range of potential inputs. The generator applies various transformations to the original images, such as rotation, flipping, shearing, zooming, and shifting. We further divided the 3264 brain tumour images dataset into training and testing sets using the 'train_test_split' function from the sklearn package. This resulted in splitting the data in such a way that 85% is in the training set and the remaining 15% is in the testing set.

Many applications of Convolutional Neural Networks require higher accuracy, and higher accuracy requires more parameters to learn and bigger networks. CNN achieve this higher accuracy by scaling up any dimension of a network (width, depth, resolution), but the accuracy gain diminishes for bigger models. It is critical to balance all dimensions of a network (width, depth, and resolution) during CNNs scaling for getting improved accuracy and efficiency. EfficientNet is a convolutional neural network architecture and scaling method that uniformly scales all dimensions of depth/width/resolution using a compound coefficient [11], [12].

We have loaded EfficientNetB3 and EfficientNetB6 models along with the weights pre-trained on ImageNet and set the include_top parameter as False to exclude the fully connected layer from the network's architecture. The fully connected layer of the EfficientNetB3 model is then redefined for our classification problem. The activation function which we applied here is 'RELU' and the dropout is set to 0.55. The final layer of our model is a fully connected layer that uses a 'Softmax' activation function and a dropout of 0.3. After the layers have been added to the model, it is compiled using the "ADAM" optimizer with a learning rate of 0.000016 and uses 'sparse_categorical_crossentropy' as the loss function. After proper training of the model on 90 epochs with a batch size of 13, an Accuracy of 96.33% is achieved with a Loss of 0.1118. Then we applied the same procedure to the EfficientNetB6 model by specifying the activation function for the final layer as “Softmax” and dropout of 0.5. After adding this layer to the model, we compile the model with the "ADAM" optimizer with a learning rate of 0.000023 and use 'sparse_categorical_crossentropy' as the loss function. After proper training of the model on 70 epochs with a batch size of 8, we achieved an Accuracy of 96.73% with a Loss of 0.1099.

V. RESULTS

In this section, we analyze the proposed model performance with the help of different evaluation metrics such as accuracy, precision, recall and F1-measure by generating the Classification report and also plotting the Confusion matrix and Accuracy Metric graph for a better understanding of results. All of the results that we obtained while working on our model are listed below.

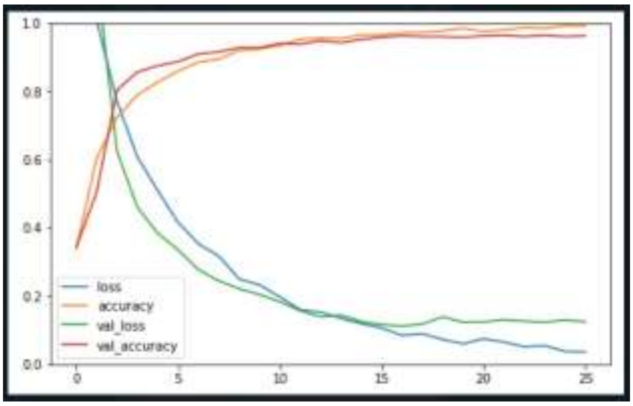

Fig. 4 : Accuracy Metrics for EfficientNetB3

	precision	recall	f1-score	support
glioma_tumor	0.96	0.93	0.95	139
meningioma_tumor	0.93	0.95	0.94	141
no_tumor	0.99	1.00	0.99	75
pituitary_tumor	0.99	0.99	0.99	135
accuracy			0.96	490
macro avg	0.97	0.97	0.97	490
weighted avg	0.96	0.96	0.96	490

Fig. 2 : Classification Report for EfficientNetB3

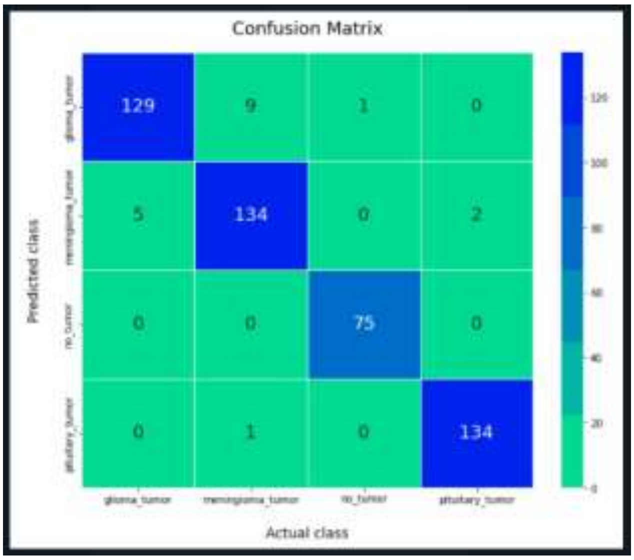

Fig. 6 : Confusion Matrix for EfficientNetB3

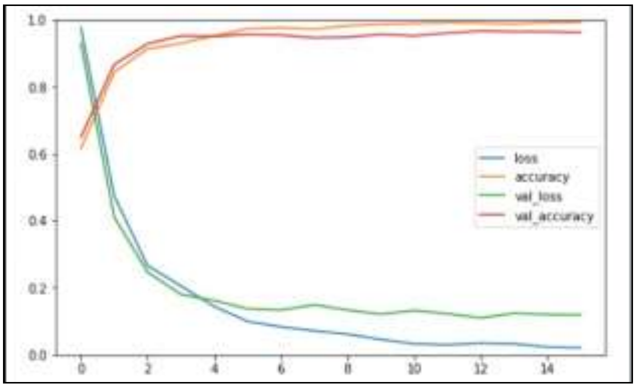

Fig. 7 : Accuracy Metrics for EfficientNetB6

	precision	recall	f1-score	support
glioma_tumor	0.97	0.94	0.95	139
meningioma_tumor	0.95	0.96	0.95	141
no_tumor	0.96	1.00	0.98	75
pituitary_tumor	0.99	0.99	0.99	135
accuracy			0.97	490
macro avg	0.97	0.97	0.97	490
weighted avg	0.97	0.97	0.97	490

Fig. 8 : Classification Report for EfficientNetB6

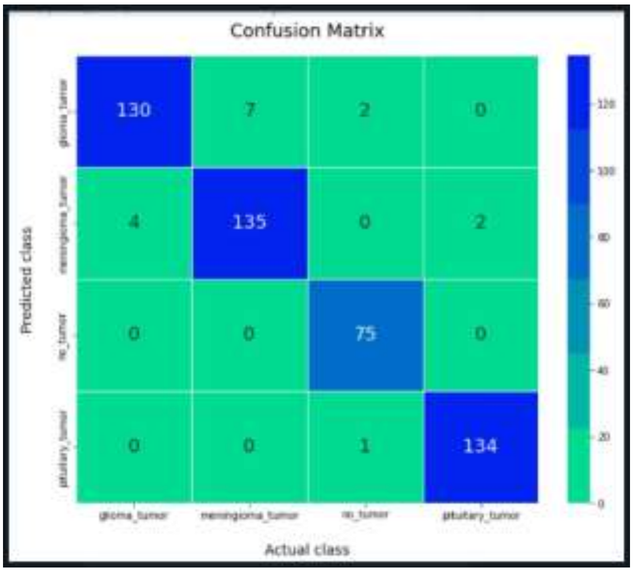

Fig. 9 : Confusion Matrix for EfficientNetB6

VI. CONCLUSION

This research paper describes the procedures for detecting brain tumours and classifying brain MRIs into meningioma, glioma, pituitary, and no tumours. To detect brain tumours, preprocessing procedures such as Grayscale conversion, Gaussian blur effect and Thresholding are used, followed by morphological operations and contour-based segmentation. This study presents an approach where we have used the Convolutional Neural Network (CNN) as the working model with EfficientNet architecture. The proposed models are evaluated using performance metrics such as accuracy, precision, recall and F1-measure. The model has a 96.73% accuracy rate in classifying various forms of brain cancers, which may help with the early detection and treatment of brain tumour.

REFERENCES

[1] Saikat Sundar Pal, Prithwish Raymahapatra, Soumyadeep Paul , Sajal Dolui, Dr. Avijit Kumar Chaudhuri , Sulekha Das, “A Novel Brain Tumor Classification Model Using Machine Learning Techniques”, International Journal of Engineering Technology and Management Sciences, March 2023.

[2] Priyanka Jain, Priyasha Parmar, “Analysis of various Pre-processing filtering methods for MRI brain tumour detection in a noisy environment”, RAEEUCCI-2022 Journal of Physics: Conference Series, 2022.

[3] Shtwai Alsubai, Habib Ullah Khan, Abdullah Alqahtani ,Mohemmed Sha, Sidra Abbas, Uzma Ghulam Mohammad, “Ensemble deep learning for brain tumor detection”, Frontiers of Computational Learning, 02 September 2022.

[4] Mohammed Rasool, Nor Azman Ismail, Wadii Boulila, Adel Ammar, Hussein Samma ,Wael M. S. Yafooz, and Abdel-Hamid M. Emara, “A Hybrid Deep Learning Model for Brain Tumour Classification”, Entropy, 2022.

[5] K. Praveena, Uriti Sri Venkatesh, Nalini Kanta Sahoo, S. V. Ramanan, M. K. Mariam Bee, N. K. Darwante, “Brain tumor detection using ANFIS classifier and segmentation”, International Journal of Health Sciences, 9 June 2022.

[6] Gangadhara Reddy P., Ramashri T., “MRI brain tumor early detection, classificationand performance evaluation using KFCM and SVM” , International Journal of Health Sciences, July 2021.

[7] Marzieh Ghahramani, Nabiollah Shiri, “Brain tumour detection in magnetic resonance imaging using Levenberg–Marquardt backpropagation neural network”, IET Image Processing, August 2021.

[8] T. Balamurugan, E.Gnanamanoharan, “Brain Tumor Segmentation and Classification using hybrid Deep CNN with LuNet Classifier”, Research Square,May 2021.

[9] K Sudha Rani , A.Suma Latha , M. Vasu Babu , S. SUNITA RATNAM, “Brain Tumour detection using Advanced Morphological Techniques”, ISSN: 00845841 Volume 53, Issue 03, March 2022.

[10] Doshi Jeel Alpeshkumar, Prof. Pinal J. Patel, Tirth Hitesh Shah, “Brain Tumor Detection and Segmentation”, Gradiva Review Journal ISSNO : 0363-8057, 2022.

[11] "EfficientNet" paperswithcode. https://paperswithcode.com/method/efficientnet (accessed Mar. 18, 2022).

[12] Tan et al. "EfficientNet : Rethinking Model Scaling for Convolutional Neural Networks" paperswithcode. https://paperswithcode.com/paper/efficientnet-rethinking-model-scaling-for (accessed Mar. 18, 2022).